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Modeling of individual egg weights of Lohmann-Brown layer hens

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Abstract: This study was carried out to determine the most suitable model for egg weights of the Cubic, Gompertz, Logistics, Gamma, Richard, Piecewise Quadratic, Orscov, and Sigmoaidal models, which are widely used in estimation. Lohmann-Brown Classic laying hens raised in Ondokuz Mayıs University Research and Application farm were used as animal material. In the modeling of egg weights of 351 layer hens raised in 3-storey cages, individual egg weight data measured at weekly intervals, 32 on the 1st floor, 17 on the 2nd floor, and 27 on the 3rd floor, were taken into account, and a total of 76 hens' individual egg weight modeling was carried out. Coefficient of determination, mean square error, Durbin-Watson, and Akaike Information Criteria values were taken into account in modeling egg weights and comparing the compatibility of models with point distribution. According to the comparison criteria, it was determined that the best estimation model was Richard. It was determined that the closest predictions to the Richard prediction model were obtained from the Logistics and Gompertz models. In addition, it was concluded that Orskov, Sigmoidal, and Quadratic piecewise regression models had the worst fit.

Key words: Egg weight, growth curve, modeling

1. Introduction

Eggs are known as a source of animal protein with high nutritional value. It is also a nutrient store rich in essential amino acids, minerals, essential fatty acids, fat and water-soluble vitamins. In addition to its nutritive value, its affordable price, rich content, and ease of consumption significantly affect egg consumption. An egg weighing 58–60 g on average is equivalent to approximately 90 g of meat or 160 g of milk in terms of nutrients. Since it has been shown in scientific studies that it does not affect blood cholesterol in humans, its consumption has been increasing in recent years. For this reason, the quality of the egg, which has a great place in human nutrition, is of great importance [1]. Egg weight, which is directly related to age and live weight in poultry, is one of the egg quality characteristics and is very important in breeding studies. Egg weight and quality are affected by many factors such as genotype, age, production system, settlement frequency, and ration. In addition, egg weight is directly proportional to the age of the hen, while yolk weight, white weight, and shell weight increase depending on age, while white and shell decrease proportionally [2].

In general, age, breed, moult, feeding method, incubation period and environmental factors are of great importance in egg weight and production amount [3]. However, regardless of the effect of age, race, moult, diet, and other environmental factors on egg weight and egg production amount, the curve they will form will show an almost similar distribution [4].

In addition to linear, quadratic, and cubic models, many nonparametric functions such as Gamma, McMillan, Richard, Schunute, Adam and Bell, Logistics, and Gloor have been applied in the modeling of egg weight curves depending on the developments in the poultry industry and computer field. Egg weight curves show a regular increase at first, then consist of three parts, after which it reaches the maximum level, and then there is a decreasing trend. In other words, in the curves of egg weights, it is seen that there is a low point at the beginning, followed by a peak where it reaches a maximum level, and then a straight line [5].

The purpose of modeling the curves of egg weights and yields is to make an early estimation of the egg weight of the current flock and to create breeding flocks. The most important factor here is to create a flock with maximum efficiency in terms of egg weight and yield. Thus, modeling and interpretation of the curves of egg weights are very important [6]. In addition, by considering these curves, the time to create the target flock in selection will decrease and naturally the degree of the target in selection will increase. However, the most important part here is the removal

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of individuals who are far below the average in terms of egg production and weight, in a model to be applied to the average of the flock. Due to the difficulties of curve modeling in terms of egg production and weight, it will be better to weed out low-yielding individuals since the average of the herd is important [7]. Thus, this approach increases the probability of selecting individuals with high genetic capacity on a herd basis [8].

It has been observed that there is a limited amount of literature on the generation of curves using mathematical models for the variation of egg weight over time. In this study, it was aimed to model the time-dependent variation of egg weights measured between 20–40 weeks in Lohmann-Brown Classic flock. For this purpose, curve estimation methods and nonlinear regression models were applied to model the changes in egg weights over time [9,10].

2. Materials and methods

2. 1. Material

2.1.1. Animal material

This study was carried out at the Research Farm belonging to Ondokuz Mayıs University, Agricultural Faculty, in Samsun, between August 2019 and February 2020, in a 3-tiers battery caged hen house. Lohmann-Brown Classic laying hens were used as animal material. Pullets were taken from a commercial firm at 16 weeks of age and a total of 351 hens were used in the study. In the modeling of egg weights of 351 layer hens raised in 3-storey cages, individual egg weight data measured at weekly intervals, 32 on the 1st floor, 17 on the 2nd floor, and 27 on the 3rd floor, were taken into account, and a total of 76 hens' individual egg weight modeling was carried out. The Lohmann-Brown chicks hatched on May 16, 2019. Sex determination, Marek, and Newcastle disease vaccination procedures were carried out in the hatchery. Beak trimming was carried out under very hygienic conditions by specially trained personnel with hot blades at 10 days of age. All management practices during the 15-week growing period were made according to the Lohmann Guide.

2.1.2. Experimental procedures

The pullets were placed in the batteries in the cage system laying house where the study was carried out at 16 weeks of age. The pullets were given a transition period of 2 weeks until the beginning of 19 weeks of age and they were expected to adapt to the new environment. The poultry house was 30 m in length, 12 m wide, and 4.5 m high. The house was artificially ventilated. The ventilation system was controlled by timers and sensors. The ambient temperature was maintained between 15 and 18 °C.

Birds were fed commercial feed containing 17.0% crude protein (CP), 2750.0 kcal/kg metabolizable energy (ME), and 2.0% calcium from 16 weeks to age at the first egg. From the first egg to 40 weeks of age, the birds were fed with a diet containing 17.0% CP, 2750.0 kcal/kg ME, and 3.50% calcium.

Until 16 weeks, 9-h light and 15-h dark program was applied and the first light stimulation was made at 16 weeks of age. The light period was then gradually increased (1-h per week) to 15-h light and 9-h dark until the hens were 21 weeks old. This program continued until the hens were 40 weeks old. Compact fluorescent bulbs used in lighting were 6500-K light spectrum (white color) and 720 lumens [11,12].

2.2. Method

2.2.1. Equations used in modeling egg weights

In this study, Cubic, Gompertz, Logistic, Gamma, Richard, Quadratic split, Orscov, and Sigmoaidal models were used to model the curves of egg weights in chickens and to estimate their parameters. Obtaining the curves and estimating the model parameters were made in the SAS package program [13,14].

The equations and expansions of these models are as follows.

Cubic piecewise regression;

$$\mathrm{Wt} = \beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{t}^2 + \beta_3 \mathrm{t}^3 + \beta_4 (\mathrm{t} - \mathrm{a})^3 + \beta_5 (\mathrm{t} - \mathrm{a})^3 \quad (1)$$

Gompertz;

$$\mathrm{Wt} = \beta_0 \mathrm{e}^{-\beta_1 \mathrm{e}^{-\beta_2 t}} \quad (2)$$

Logistics,

$$\mathrm{Wt} = \beta_0 / (1 + \beta_1 \mathrm{e}^{-\beta_2 t}) \quad (3)$$

Gamma,

$$\mathrm{Wt} = \beta_0 \mathrm{t}^{\beta_1} \mathrm{e}^{-\beta_2 t} \quad (4)$$

Richard,

$$\mathrm{Wt} = 1/\beta_0 + \beta_1 \mathrm{e}^{(\beta_2 t)(-\beta_3)} \quad (5)$$

Orskov,

$$\mathrm{Wt} = \beta_0 (1 - \mathrm{e}^{-\mathrm{c}} \mathrm{t}) \quad (6)$$

Quadratic split,

$$\mathrm{Wt} = \beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{t}^2 \quad (7)$$

Sigmoidal,

$$\mathrm{Wt} = \beta_0 / (1 + (\beta_1 / \mathrm{t}))^{\beta_2} \quad (8)$$

Here;

W_t : t. weight over time,

β_0, β_1, β_2, β_3, β_4 ve β_5 : Constants defined for the models,

a, b, and c : Node points in piecewise regression,

e : 2.7182,

t : It represents time.

2.2.2. Model comparison criteria

In the modeling of egg weights, coefficient of determination (R^2), mean squares of error, Durbin-Watson (DW), and Akaike information criteria (AIC) were taken into account in comparing the compatibility of the models with the point distribution [15].

2.2.3. Coefficient of determination (R^2)

The R^2 value shows how much of the total variation in the data set can be expressed by the model fitted to the point distribution and takes values in the range of $0 \leq R^2 \leq 1$. A high coefficient of determination means that the model obtained is well suited to the point distribution.

The coefficient of determination is calculated as in Equation 9.

$$R^2 = 1 - (SSE/SST) \tag{9}$$

Here;

SSE: Error sum of squares,

SST: Total sum of squares is in the form.

2.2.4. Error mean squares

The low mean of squares of error indicates that the model is highly suitable for point distribution. Therefore, it is widely used in model comparisons (Soysal et al., 1999; Aydın et al., 2018). PLA is calculated as in Equation 10.

$$MSE = SSE/(n - p) \tag{10}$$

In the equation, SSE: Error sum of squares, n: The number of observation pairs, p: The number of parameters in the model [16].

2.2.5. Akaike information criteria (AIC)

The Akaike information criterion value is a widely used criterion in choosing the most statistically appropriate one among the equations created. As a rule, the model with the smallest AIC value is considered to be the most suitable model and the AIC is calculated as in Equation 11.

$$AIC = n\,x\,ln\left(\frac{SSE}{n}\right) + 2k \tag{11}$$

In the equation, SSE: Error sum of squares, n: Number of observation pairs, k: Number of parameters in the model, ln: log10 base [16,17].

2.2.6. Durbin-Watson autocorrelation test (DW)

It is a test to test whether the error terms of the predicted model are in correlation. The fact that the value obtained with this test is around 2 is a strong indication that there is no autocorrelation. The DW value is always between 0 and 4. If the DW value is 2, it is accepted that there is no autocorrelation [18,19]. DW value is calculated as in Equation 12.

Here e_i = Error term, t = Time.

$$DW = \frac{\sum_{t=2}^{n}(e_1 - e_2)^2}{\sum_{t=1}^{n} e_1^2} \tag{12}$$

3. Results and discussion

In the modeling of egg weights of 351 layer hens raised in 3-storey cages, individual egg weight data measured at weekly intervals, 32 on the 1st floor, 17 on the 2nd floor, and 27 on the 3rd floor, were taken into account, and a total of 76 hens in R^2, AIC, and DW values of the curve models calculated using Cubic, Richard, Logistics, Gompertz, Orscov, Sigmoidal, and Quadratic piecewise regression, which are among the individual egg weights of the chickens used in the study, are given in Table 1, Table 2, and Table 3.

When the MSE, R^2, AIC, and DW values for all individual models of eggs obtained from animals in the first layer are examined in Table 1, it is seen that Richard, Logistic, and Gompertz models have the best results and very close values are obtained. Orskov and Quadratic piecewise regression seem to give the worst results. When the comparison criteria for all individual models of eggs obtained from animals on the second floor are examined in Table 2, it is seen that the Richard model gives the best results, while the Sigmoidal and Quadratic piecewise regression models give the worst results. In Table 3, when the comparison criteria for all individual models of eggs obtained from animals on the third floor are examined, it is seen that the Richard model has the best results, while the Orskov and Quadratic piecewise regression models give the worst results. Thus, when Table 1, Table 2, and Table 3 are examined, it is seen that the best model is

Table 1. Comparative values of individual models of eggs from first-floor animals.

Models	n	MSE		AIC	DW
Cubic Piecewise Regression	32	14.886 ± 0.2	0.822 ± 0.2	–13.5 ± 2.33	2.79 ± 0.5
Richard		14.059 ± 0.5	0.997 ± 0.2	–63.9 ± 1.96	2.06 ± 0.9
Logistics		14.129 ± .01	0.997 ± 0.2	–42.6 ± 2.33	2.09 ± 0.5
Gompertz		14.051 ± 0.7	0.997 ± 0.1	–42.3 ± 1.14	1.97 ± 0.7
Orskov		20.322 ± 0.5	0.996 ± 0.1	–16.5 ± 1.11	2.86 ± 0.6
Sigmoidal		14.912 ± 1.1	0.997 ± 0.4	–13.7 ± 1.02	0.36 ± 0.3
Quadratic Piecewise Regression		14.253 ± 1.5	0.794 ± 0.7	–9.92 ± 1.9	3.11 ± 0.8

Table 2. Comparison values of individual models of eggs from animals on the second floor.

Models	n	MSE		AIC	DW
Cubic Piecewise Regression		3.970 ± 0.3	0.886 ± 0.1	–12.4 ± 1.21	2.85 ± 0.7
Richard		5.382 ± 0.2	0.999 ± 0.2	–53.9 ± 2.31	2.01 ± 0.5
Logistics		6.600 ± 0.3	0.9980 ± 0.1	–40.6 ± 2.22	2.38 ± 0.7
Gompertz	17	6.435 ± 0.1	0.998 ± 0.3	–33.3 ± 3.15	1.81 ± 0.8
Orskov		8.744 ± 0.5	0.998 ± 0.3	–16.5 ± 2.98	2.91 ± 0.9
Sigmoidal		14.886 ± 0.9	0.999 ± 0.4	–13.7 ± 3.97	0.31 ± 1.1
Quadratic Piecewise Regression		7.465 ± 0.2	0.741 ± 0.2	–0.94 ± 1.98	3.36 ± 0.9

Table 3. Comparative values of individual models of eggs from third-floor animals.

Models	n	MSE		AIC	DW
Cubic Piecewise Regression		5.420 ± 0.3	0.884 ± 0.4	–11.1 ± 4.5	2.99 ± 0.5
Richard		6.182 ± 0.2	0.999 ± 0.3	–83.2 ± 3.1	2.07 ± 0.7
Logistics		6.653 ± 0.3	0.998 ± 0.7	–51.6 ± 2.9	2.48 ± 0.5
Gompertz	27	6.594 ± 0.4	0.998 ± 0.5	–49.3 ± 3.2	1.71 ± 0.4
Orskov		11.467 ± 0.5	0.997 ± 0.4	–19.5 ± 2.1	3.12 ± 0.4
Sigmoidal		14.886 ± 0.7	0.999 ± 0.3	–14.4 ± 1.9	0.55 ± 0.5
Quadratic Piecewise Regression		7.000 ± 0.5	0.818 ± 0.7	–0.71 ± 1.7	3.01 ± 0.7

the Richard model. It is seen that the closest estimates to the Richard model are obtained from the Logistics and Gompertz models. Orskov, Sigmoidal, and Quadratic piecewise regression models were found to have the worst results. Figure 1, Figure 2, and Figure 3 show the curves obtained from the individual growth curves of Cubic, Richard, Logistics, Gompertz, Orscov, Sigmoidal, and Quadratic piecewise regression models.

When the value of the increase in egg weights of the chickens used in the study and the coefficients estimated using the individual growth curves of Cubic, Richard, Logistics, Gompertz, Orscov, Sigmoidal, and Quadratic piecewise regression models, the values of MSE, R^2, AIC, and DW are examined, the best model is the Richard model and the worst model is the Orskov and Quadratic piecewise regression model. Obtained results [20], [21], and [22], are in agreement with the studies. In their study, they showed that the best model for comparing Cubic, Gompertz, Logistic, Richard, Schunute, and Quadratic Spline models is Richard, Gompertz, and logistic models. In addition, [20] and [23] stated that the best model among the Gompertz, Logistic, and Von Bertalanffy models is the Gompertz model in their work on modeling egg weights. Similarly, [20] reported that the best model was the Gompertz model by examining the parameters known as brood body weight and maximum growth rate in their study. It was seen that the results obtained were compatible with the studies carried out.

4. Conclusion

In this study, some of the most used models for modeling egg weights in chickens were examined comparatively. When the MSE, R^2, AIC, and DW values of the curve models created for egg weights were examined, it was concluded that the Richard model gave the best results, while the Orskov and Quadratic piecemeal regression model gave the worst results.

In addition, in this study, as a result of the individual growth curves of Cubic, Richard, Logistics, Gompertz, Orscov, Sigmoidal, and Quadratic piecewise regression models and the curves of individual egg weights obtained from different cage layers, it was seen that the best curve modeling was the curves obtained from the eggs in the third layer. At the same time, it was determined that the results were very close to each other in the other curves. The point to be considered here is that the fluctuations in the point distribution of the curves can be tolerated by increasing them.

Modeling the point distributions of egg weights on the basis of herds in most enterprises seems to be very important

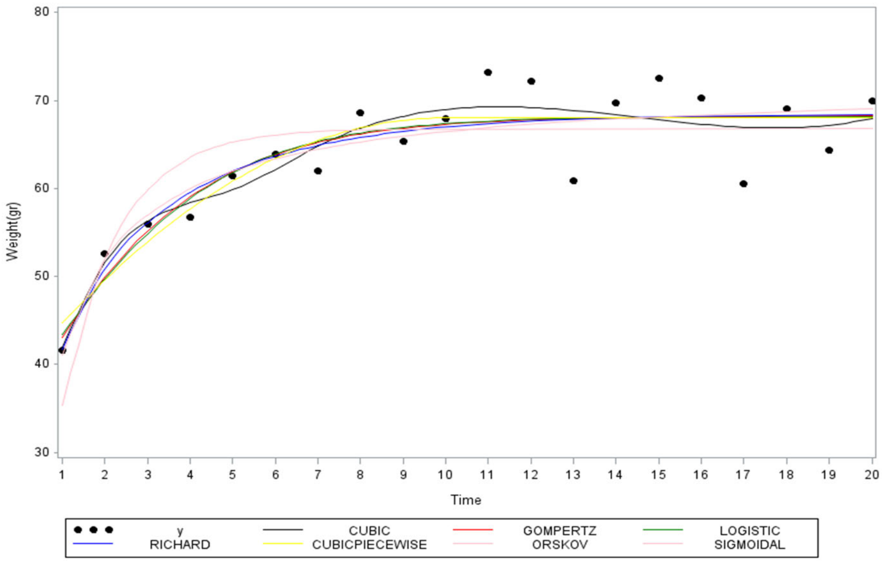

Figure 1. Curves for individual models of eggs from first-floor animals.

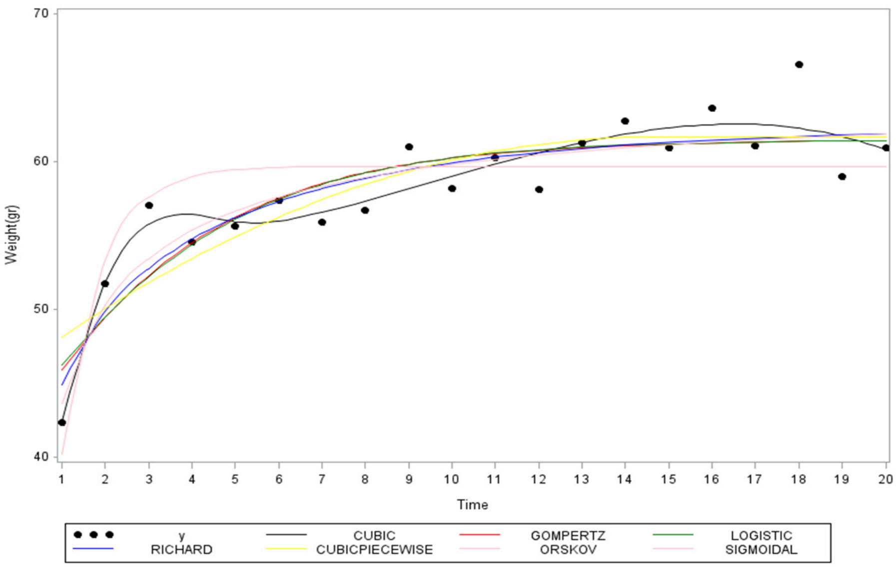

Figure 2. Curves for individual models of eggs from animals on the second floor.

when the issues such as yield, herd management, care, and feeding conditions are addressed. For this purpose, the part that should be considered in the selection of the model is that a good literature review should be done first, and then the tendencies of the models in forming curves and their biological interpretation. For this reason, having as many model comparison criteria as possible and a general interpretation of these criteria in model selection will help the researcher to determine the most suitable model statistically.

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All data sets collected and analyzed during the current study are available from the corresponding author (K. Erensoy) at a reasonable request.

Availability of data and materials

All data sets collected and analyzed during the current study are available from the corresponding author upon reasonable request.

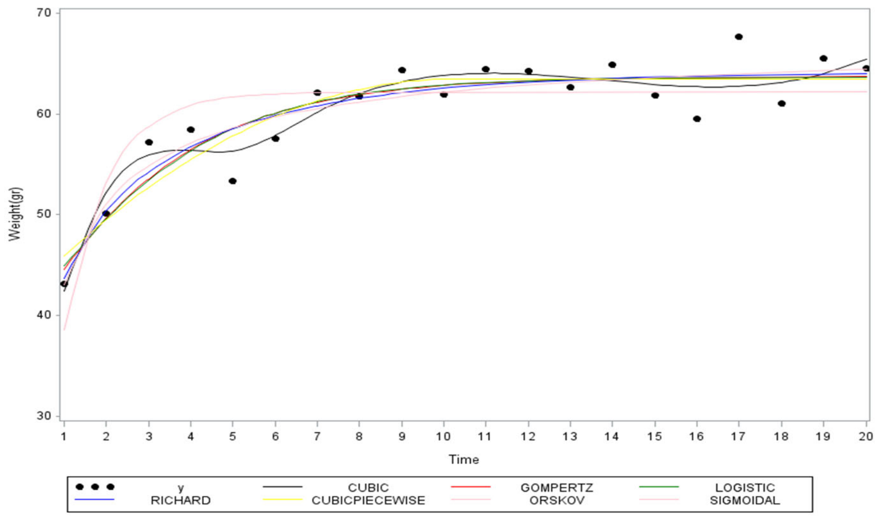

Figure 3. Curves for individual models of eggs from third-floor animals.

Author contributions

E.Y.: initiated the research idea, developed, organized, analyzed, and interpreted the data, and wrote the manuscript. S.H.A.: developed the research idea, structured the paper, and edited the manuscript. K.E.: created and edited data, M.S.: suggested the research methods, structured the paper, and edited the manuscript.

Conflict of interest

The authors declared that there is no conflict of interest.

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